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MUSA–I. towards New Social Tools for Advanced Multi-Modal Transportation in Smart Cities †

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† Presented at the 12th International Conference on Ubiquitous Computing and Ambient Intelligence (UCAmI 2018), Punta Cana, Dominican Republic, 4–7 December 2018.

Published: 19 October 2018

Abstract: Urban mobility optimization problem has a great focus in the context of Smart cities. To its solution a very important factor is the transport demand, which is mostly inferred using Big Data and Artificial Intelligence techniques from Automatic Fare Collection (AFC) and mobile devices data. In this paper a novel approach, based on Transport Demand Management techniques is proposed, using technology to produce a more active social involvement in the planning and optimization of mobility. This paper describes, a first step to this long-term objective, the general architecture and current implementation of an explicit multi-modal transport demand system for Smart Cities, which is being developed in the frame of MUSA—I project in the city of Madrid.

Keywords: smart cities; explicit demand; bus sensorization; smart bus stops

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1. Introduction

1.1. Towards New Social Tools for Advanced Transportation in Smart Cities

The urban mobility optimization problem can be addressed from several sides at the same time, developing original architectural or urban planning and developing and applying new technological systems and social systems.

The approach described in this paper belongs to the second option. To optimize mobility resources at least four factors can be highlighted: (a) transport demand; (b) transport management; (c) transport state; and (c) disruptive procedures and technologies that can improve the actual transport flow.

Currently, transport demand is mostly inferred using Big Data and Artificial Intelligence techniques from Automatic Fare Collection (AFC), tracking mobile devices positions and, in a lesser degree, using mobile apps and social networks. This type of interaction is mainly passive from users' point of view. In this paper, a more active interaction is foreseen through the explicit declaration from users of their demand and the possibility of implement Transport Demand Management techniques [1] e.g., planning staggered traveling.

A factor crucial for this model is the adequate sensorization of all multimodal means of transport to know their state. In our vision, this also includes the development of smart bus stops and train stations that help to characterize and measure the actual transport flow in the city. Once passenger demand and transport flow are measured and put into a robust model, a better understanding, application and assessment of disruptive procedures and technologies can be performed (what-if scenarios).

This paper describes, a first step to this long-term objective, the general architecture and current implementation of an explicit demand system for Smart Cities' buses, which is being developed in the frame of first MUSA project ("Mobiliario Urbano Sostenible y Avanzado" or Advanced Sustainable Urban Furniture).

1.2. The Transport System

Figure 1 describes the concept of the transportation system used in this paper. In the center, the state of the transport system (the state of vehicles, trains, roads, railways, etc.) is used to plan the demand of transport for users (passengers and private drivers) and for authorities to manage the state of transport (traffic lights signaling, cameras, sensors and actuators). On the other hand, a set of transport providers is interacting with the system: bicycles, trains, metro, buses, tram, taxis, pedestrians and advanced providers as: shared transport, collaborative transport, on-demand transport, autonomous vehicles, etc.

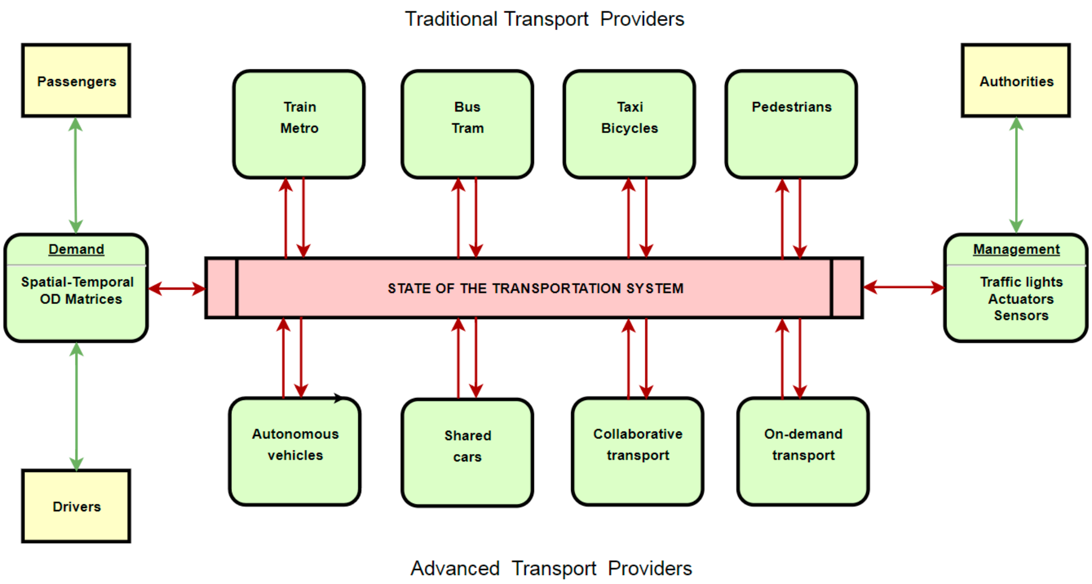

Figure 1. General concept of the transport system used in this paper.

1.2.1. Transport Demand Modeling

For modelling transport demand, there are several methodologies:

1. Trip-based model or classical four steps model [2] which estimates the number of trips for different travel modes and routes taken between any two origin and destination zones.
2. Activity-based model, which predicts for each individual the desired number and sequence of activities and its required trips in a given time with a set of spatial, temporal and resources constraints. These individual activities are aggregated in origin-destination-matrices (OD data) for planning transport operations.
3. Agent-based model. This method, founded on activity-based modelling, employs traffic simulation of agents for each individual demand, taking into account constraints of transport network [3]. Examples of agent-based tools are TRANSIM [4], SimAGENT [5], MATSim [6] and SimMobility [7]. These tools allow the modelling and analysis of time- and demand-dependent pricing, as well as new forms of mobility such as shared and autonomous vehicles.

1.2.2. Demand Modeling Data Sources

As it can be noticed, advanced methodologies are based on individual trips, which can be mined using Big Data techniques from these data sources:

1. Smart Card Automatic Fare Control (SC-AFC) data
2. Smart phone and embedded GPS data
3. Points of Interests (POI) information
4. Census and Survey
5. Land use information

Smart Card Automatic Fare Control (SC-AFC) data jointly with mobile phone and embedded GPS data are the main source of information for mining individual trips.

Smart Cards are widely used in public transport networks and provide information about boarding time and station, vehicle identification (mainly buses and trams) and alighting time and stations (mainly for trains). In some cities as Singapore and Amsterdam, the transport charge is based on total distance for train and buses, so passengers use their cards at entry and exit point of public transport system. In these cases, more information can be obtained than in cities like London or Madrid, which use a flat rate (card is not always used at exit point).

There are many algorithms and techniques for mining SC-AFC data and reconstructing trips [8], travel modes [9–11] activity identification [12,13] and agent-based transport models and simulation as Bouman [14] for Amsterdam and Rotterdam and Fourie, Erath, Ordóñez Medina, Chakirov and Axhausen [15] for Singapore's public transport.

Smart phone and embedded GPS data provides information about individual trips, which is mined from the data produced by two main types of events: network-triggered location updates (i.e., during a handover, when during a call the phone move between two different cells) and event-triggered updates (i.e., when a call is received or placed). Some applications use these two main events for data mining while other use CDR or Call Detail Record (the data used in telecom companies for billing purposes).

There are many algorithms and techniques for mining mobile phone data and discover OD data and activities [2,16,17], for discovering places related to general activities as home, work, leisure, shopping, etc. [18], for discovering transport modes [19] and for modelling San Francisco Bay Area mobility applying agent-based simulation in MATSim based on anonymized CDR records [20].

Points of Interests (POI) information allows to infer other activities beyond primary locations (home, work, study). Noulas and Mascolo [21] infer other activities (Arts, Entertainment, Shops, Food, Work, etc.) using CDRs and Foursquare data. Similarly, Phithakkitnukoon, Horanont, Di Lorenzo, Shibasaki and Ratti [22] infer activities using POIs extracted from Yahoo maps.

Census and Surveys provide information about demography, health, communication and transport, etc., which are used to validate home and working areas, city hotspots, traffic flows and validate land use. These data have a good spatial resolution but are updated usually in intervals of several years.

Land Use datasets provide information that characterize an area of the city based on its planned and effective land use and can be used to validate activities mined from SC-AFC and mobile phone data.

1.3. State of the Transport System

For modelling the traffic flow several approaches has been used, for example traffic assignment models as discussed in [23], where network models are used to allocate traffic loads to routes. These models are static and then it is not possible to make vehicle movements explicit; in fact, only load capacities are modelled, while the current transportation performance is not considered. Other interesting approach is the application of Max-Plus algebra to transportation systems as described in [23], the focus is on synchronization of vehicle's arrivals and departures at local points in the network. The dynamics induced by passenger movements are not included in this approach. At the other hand, Petri nets style models also are used to model traffic as for example in [24].

High-quality information systems both on vehicles, as public buses, and in road infrastructure are also important for better citizen's mobility. The increased communication, between the vehicles and the infrastructure, and between vehicles, offer opportunities for flexible and innovative traffic solutions. On the other hand, the more there is automation in the vehicles, the more they can provide accurate sensing measurements that could also be used for a better traffic control.

There are several visions of vehicular communications, generally called Vehicle-to-2 (V2X) systems, including vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), vehicle-to-cloud, (V2Cloud) and internet of vehicles (IoV). A common term to describe the systems where vehicles communicate with the infrastructure and each other is cooperative systems or cooperative Intelligent Transport System (C-ITS). In the past few decades, there has been growing interest in getting vehicles as active participants in the traffic control and information sharing as is extensively described in [25]. Now, in the era of Smart Cities, the urban buses have a major role in the quality of life of the citizens. In general, they are equipped with at least Global Positioning System (GPS) equipment, so their location can be tracked in real time, but it is important to gathering more data about the passengers and their travel routines for a better understanding of urban mobility. In this sense, next generation public buses need more sensors, as for example smart ticketing including biometric recognition, destination selection, counting passengers that drop off, tracking the number of passengers of the bus in real time, mobile phone chargers and information devices

This vehicle information also need to be coordinated with Bus stops. There are several efforts in this sense, for example Barcelona's smart bus stops are connected to the city's fiber-optic backbone network. They display online bus running schedule, information for foreign visitors, shows advertising and important events, USB charging points for mobile gadgets, such as smart phones, laptop, ipod, tablets, while provide free Wi-Fi hotspots, giving waiting people access to the Internet using their mobile devices [26].

Indicators of common use, such as passenger count, travel speed, time of transport of passengers, locations of and the measurement of time, are being increasingly completed with other more sophisticated measures, such as real-time levels of occupation of the means of transport or the adequacy of the trip to the user's needs [27]. In this context, there has been a growing interest in the development of tools based on analysis of additional data, such as social media (providing access to valuable information), incident detection, mobility and activity patterns complemented with analysis of opinions of the users [28,29]. The integration of different sources of information also plays a key role for multimodal public transport, which reduces the complexity of public transport networks while considering all the different modes of transport (e.g., metro, bus, cycling, walking or car sharing) [30].

2. Materials and Methods

It can be noticed that most of demand modelling studies are based on data mining extracting meaningful information about demand activities. This information is used to characterize demand and to run agent-based planning and simulation.

In this paper, a different, long-term Transport Demand Management (TDM, also known as Mobility Management) strategy [1] is envisioned. Instead of mining data of passengers, an application allows them to explicitly reserve and plan their trips. To increase the effectiveness of this approach, in addition to a software application, two complementary systems are being designed: (a) increased sensorization of buses installing Automatic Passenger Counters (APC) to know the occupancy of the bus in real time, the availability of free places for wheelchairs and baby-strollers and the flow of passengers in each bus stop and (b) the design of smart bus stops, which are a very special Point of Interest (POI), is analyzed from social, architectural and technological points of view. Research about possible smart stop services are being performed. This can include not only public and private transport services, but community communication services, publicity services, environment and health services, etc. Figure 2 shows the MUSA—I architecture.

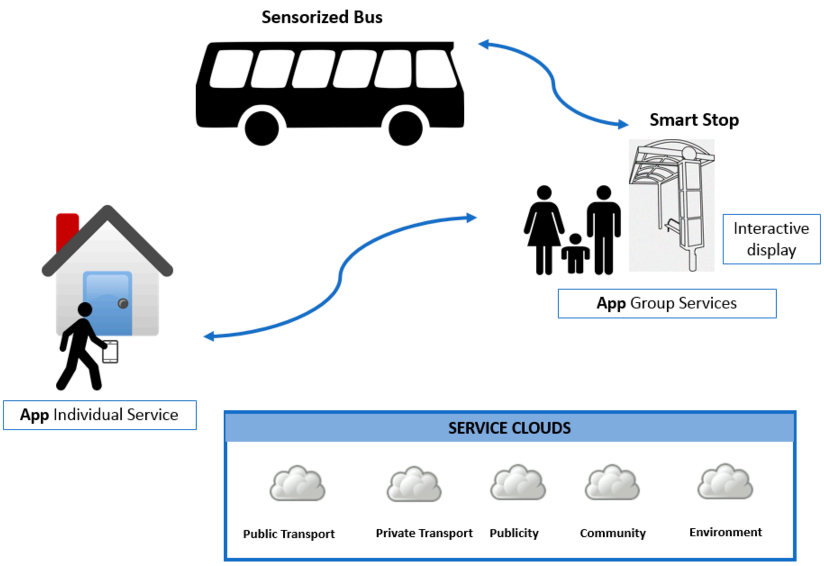

Figure 2. Main components of MUSA—I architecture.

The software application will be available in two versions, as an individual service in passengers' mobile phones and as a group service on smart stops screens. **The application allows the multi-modal planning of trips including walking, cycling, taxis and public transport. It is running on Google Maps and it is customized for individual users.**

Madrid buses are already sensorized with ALV (Automatic Vehicle Location) using GPS and SC-AFC (Smart Card Automatic Fare), the next level of sensorization planned is the use of APC or Automatic Passenger Counters. There are different technologies for APC, being the most used infrared systems and vision system (video cameras, stereo cameras and Time-Of-Flight cameras). Though for this project, infrared systems and stereo cameras were studied, we used simple video cameras from Retail Sensing, a Manchester company, to evaluate their performance in real-life conditions. The cameras located on top of front and rear door use artificial vision algorithms to count in and out passengers. This information is sent through a 4G router to an MQTT server to make it globally available.

First, we tested them on Lab, then we installed then on buses and currently we are finishing the testing during daily operation of a bus in the center of Madrid.

The smart bus stop is being designed as a smart furniture, which provides different services: information about public and private transport, reservation of trips, as well as publicity services, community communication services, environment awareness information and delivering point for e-commerce. These services can be accessed from a screen available in the stop which will connect passengers to a set of cloud services (Figure 2). The works on smart stop are currently in progress.

3. Results

The APC system is currently being tested and adjusted on a bus in the center of Madrid. A web app allows to visualize the number of daily passengers using the bus, as well as the behavior of passenger flow in each stop. The works on smart stop are currently in progress, while the development of the app is running on the planned schedule.

4. Discussion

New technologies can be used to improve the traffic flow in cities, and a better public transportation service can be provided to make more travelers choose public transportation, reducing the pollutions levels and improve the citizen's mobility.

Instead of mining data of passengers, an application can allow them to explicitly reserve and plan their trips. So, passengers are converted from a passive role, which just try to fit their demand in the transport system, into an active role able to modify the system with their demand. Active planning can be used to stagger trips reducing the load on the transport system and decreasing trip time of passengers. This reservation is anonymous, the app just specifies a place being required on transport system during a given interval of time. This approach can be seen as a generalization of on-demand transport (on-demand mobility) concept to the whole transportation system. Of course, it is a long-term approach that needs the involvement of the city authorities and its population to re-organize working life and therefore transportation into a more rationalized and efficient activity. In this paper, the first steps toward such goal are started.

5. Conclusions

This paper describes the first steps of a novel, long-term, system that combines new technologies and social involvement for optimizing mobility resources. This step focused on buses is currently in development. The complete sensorization of buses in Madrid is already an official plan of Municipal Transport Company, so it is foreseeable that these data can be soon available through Open Data databases of the company. We hope that development of Smart Bus Stops converts them into a very important spot from the transport planning view as well as from citizen life point of view. This jointly with multimodal transport apps under development will ensure a more efficient planning and future reserve of trips using TDM techniques.

Author Contributions: Conceptualization and Methodology, V.M.P.N., M.d.B.R., D.G.P. and J.L.E.P.; Software, A.G.G.-O., A.L.P. and V.M.P.N.; Investigation and Validation, M.d.B.R., D.G.P., J.L.E.P., V.M.P.N., A.G.G.-O. and A.L.P.

Funding: This research was funded by Universidad Europea de Madrid grant number 2017/UEM22.

Acknowledgments: We want to express our deep gratitude to all those persons and institutions that are helping and supporting us in the realization of this project. We want to thank the institutional support from "Universidad Europea de Madrid", from the Municipal Transport Company (EMT) of Madrid, for the kindly support of its executives and technical staff; and at last, but not at least, to Asad Syed from Retail Sensing for his kindly support and sponsorship with the APC system. To all of you, thank you very much.

Conflicts of Interest: The authors declare no conflict of interest.

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